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THE METHODOLOGY AND MYTHOLOGY OF COMPUTER SIMULATIONS

by

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INTRODUCTION

The use of general purpose computers for systems
simulations will become more widespread because of increases
in computational speed and new developments in high level
languages. It is the intention of this paper to focus on
some of the fundamental methods used in digital simulations
and thereby expose some of the myths.

METHODS OF MODELING AND SIMULATION

Simulation and modeling as a means of problem solving
have always been used by man. An early example is man's
attempt to model the shape of the earth. Since he could
only observe that the horizon appeared to be a straight
line, one model for the earth's shape was that of a finite

plane. Another model, not too popular at the time, was that
of a sphere. These models were necessary to construct in
order to project what might happen if one sailed farther
than the eye could see. As we know, a voyage (or experiment)
eventually had to be conducted in order to validate the
model.

Today, simulation and modeling still involve those
same basic concepts, although we have at our disposal a
large array of technological innovations to help us in this
job. Simulation, modeling, experimentation, and analysis
are all dependent on each other, and we should keep upper-
most in our mind that the proper mix is essential to any
reasonable research and development program.

MODELING

In order to gain a clearer view of simulation and
modeling, modeling will be defined as a subset of simulation.
Modeling is then divided into the two broad categories of
physical models and mathematical models:

a. Physical Models

Physical models are an attempt to reproduce the
phenomenon of interest in an exact form to the same scale
or some other scale. A couple of examples as shown in

Figure 1 should suffice.

A scale model submarine is subjected to flow studies in a water tank, data on drag and lift forces is collected, and empirical formulas are developed to aid in performance predictions. The physical model in this case is the scale model submarine.

A general purpose computer is used to simulate some special purpose digital hardware. Data is obtained on logic flow, register sizes, and truncation errors. The physical model in this case are the internal registers scaled to act as small registers.

b. Mathematical Models

Mathematical models will be further dissected into the two categories; deterministic and stochastic for illustrative purposes:

(1) Deterministic Mathematical Models

The average engineer is probably most aware of the deterministic model since these were used most extensively in his undergraduate training. One example should suffice. Consider the response of the RC circuit in Figure 2 to a voltage input. Here a differential equation for this circuit determines the exact voltage output at any

point in time for a particular input. This equation then
is a deterministic model of that circuit; insofar as the
main voltage characteristics are concerned. The accuracy
of the solutions are dependent on the computing machinery
and the programming techniques.

(2) Stochastic Mathematical Models

The stochastic type of mathematical model is
not so well known. Associated with this model is a name
"Monte Carlo", due to the use of random sampling in these
models. Two elementary examples will illustrate the two
basic variations used.

In the first example we are required to
evaluate the following definite integral:

$$y = \int_0^1 (x)\,dx \qquad\qquad (1)$$

The Monte Carlo method of solving this integral
is to obtain an ordered pair of random samples from a
uniform distribution between 0 and 1. The first sample is
considered to be the x (abscissa) value and the function of
x is computed. If the second sample from the ordered pair
is less than the computed value (less than x in this case)
a success or Yes decision is indicated. If it is greater

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than x then a failure or No decision is indicated. The
success and failure regions are indicated in Figure 2. The
ratio of successes to total trials now gives us an estimate
of the integral. Out of 100 tries we might have 51 successes,
thus our answer would be 0.51. As we know, the correct
answer is 0.5. However, we may increase our trials to further
reduce the inaccuracy.

The second example is an illustration of the
second variation of the "Monte Carlo" technique. Here
the model is _event_ oriented. Let us suppose we are studying
the flow of people through a check-out counter at a super
market. Figure 3 illustrates the process. We ask the
question once every second if someone is waiting to be
checked out. This is the first event. The answer is
provided by the throw of a pair of dice (a random sampling
technique) and some decision rules. When there is someone
waiting, the checker will proceed to start checking the
items. This is the second event. We now ask the question
whether the customer is finished checking, (or the second
event). Again the answer will be determined by the throw
of the dice and some other decision rules. This process
is repeated many times over and one can find answers to the

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questions, "How many people on the average are waiting?";
"How long does it take to get checked-out?". Of course
our answers will be dependent on how many items we assume
the customer has in the cart, (these are our decision rules
in the checking process). How valid the model is, is
dependent on the validity of the decision rules. Hence,
we may study at will under what conditions it is wise to
open up another counter.

        The above examples are certainly not
2.
exhaustive. There are many good references available.

SIMULATION

Since models are a subset of simulations, any or all
of the types of models described maybe used singularly or
together, in a simulation. The way in which the models are
interconnected with each other, and with humans, allows us
to dissect simulations into the three main classes; fully
automatic, semi-automatic, and integrated.

A fully automatic simulation is a hands-off type of
simulation in which the process is under complete computer
control. The simulation is left free to run for a period
of time without human intervention and the results are
then inspected. The study of a special purpose computing

hardware previously mentioned is such an example.

In the semi-automatic type of simulation critical
decisions on parameter values, or plain value judgements
are entered directly into the simulation when needed. If
in our super market example the decision to open up another
counter was made by a human, and the process continued,
such a simulation would be known as a semi-automatic
simulation. The results of course are heavily dependent
on the person engaged in the simulation.

The integrated type of simulation generally involves
the computer control of special purpose devices or
physical models and the interaction of humans. Such a
simulation might involve the testing of a large system
under controlled inputs. An example is a simulated Apollo
count-down.

A variety of high level computer languages have been
developed to aid in computer simulations by allowing one
to easily specify models of various types in an easy
fashion. A recent tabulation in the IEEE April Transaction
on Computers, show 20 such translations in use. One example
of an event oriented language is "GPSS" or general purpose
system simulator. An example of a digital hardware

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simulation language is "MIMIC", developed at Wright

Patterson Air Force Base.

In summary, computer simulations are essentially a

very special type of experiment in which the basic build-

ing blocks are models of small aspects of the total system.

The attractiveness is that system performance may be observed

as slight changes are made in the models.

CRITERIA FOR APPLICATION

"When should such a tool be used?", is a frequently

asked question. The answer will be divided into three

parts:

a. A simulation should be used if analytical methods

fail to exist, or are not as efficient as a simulation, and

all other approaches have been explored. Analytical methods

and problems do not always exist side by side.

b. A simulation should be used if we have reasonable

assurance that sufficient data exists to give realism to

the built-in assumptions of our models and data basis.

c. A simulation should be used if the process of

constructing and running the simulation can be a beneficial

learning experience.

There are at least two applications to sonar technology

that stand out as examples of a good application of
simulation techniques.

a.   The first example is the simulation of prospective
digital hardware for sonar systems. The UNIVAC 1108 at NUSL
has a powerful repertoire of machine instructions to be put
to advantage. Such simulations allow one to gain confidence
in the specification of reasonable experimental sea going
hardware, by exercising a physical model. The adaptive
beamforming algorithms have many questions concerning
sensitivity to hardware implementation.

b.   The second is the application of simulation to the
sonar design problem. Characteristic of this problem is
the interaction between many parameters, and the manipulation
of large data bases. A semiautomatic simulation with the
designer operating in an interactive environment would
relieve the designer of the tedious bookkeeping that is a
large part of the design job. Interactive, of course,
implies some type of graphic computer terminal. Such a
simulation would allow the design of sonar systems on
more than a first order statistical basis.

Summarizing this section, one finds that the applica-
tion of simulations to a specific job is really understand-

ing the capability of the resources available, the problems
at hand and then providing a heavy does of common sense to
match the two.

THE ANALYSIS OF RESULTS AND THE MYTHS IN SIMULATIONS

No model, be it physical or mathematical, can
accurately model all the effects or parameters of interest.

In the deterministic RC circuit equation of Figure 2,
the thermal voltage generated by the resistor was ignored.
Models must be validated against real data.

Our first example of modeling the earth in this paper
pointed out this important fact. Eventually an experiment
(voyage) had to be run in order to validate the two
reasonable models of a flat world, and a round world. This
aspect of model validation cannot be overemphasized.

Failure at model validation has generated a simulation
mythology. A myth, as used here, is defined by Webster as
a "belief given uncritical acceptance by the members of a
group, expecially of existing or traditional practices
and institutions." This will probably always arise in
simulation work because of its very nature. Let us list
a few reasons at why myths are developed.

First, a semi-automatic simulation invariably gives
different answers depending on the value judgements and
parameter values used by the operator. This is exactly
what was intended, of course, but it generates the myth:
"One never gets consistent results from a simulation."

Second, simulations that involve the stochastic event
type model generate the same type of myth due to their
nature of traveling different probability trees. However,
this is what the designer intended. It is this aspect which
is to be studied.

Third, and perhaps the most common error in simulation,
is to use existing models to evaluate a different set of
parameters than originally intended. This gives rise to
the often heard myth: "Simulation results will never agree
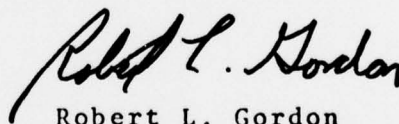with any real life experience."

These and other myths in computer simulation work can
be held to a minimum only if the results, assumptions,
parameters, and judgements built into each and every model
in the simulation is critically inspected for departures
from real life experience, and such departures clearly
documented. It is realized that it is not human nature to
document the weaknesses of ones work. However, documenta-

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tion has the important benefit of pointing up those areas
where knowledge is lacking and more effort should be
employed.

CONCLUSIONS

Since simulations are only limited by man's
ingenuity in developing modeling techniques and systems of
models, it has been difficult to treat adequately such a
broad subject in so short a space. Successes at treating
complex problems by simulation methods has opened up the
danger of viewing simulation as a panacea for all complex
problems. It is not. Only common sense and the proper
mixture of analytical experimental and simulation work
will result in a successful attack on tomorrow's problems.

Robert L. Gordon

REFERENCES

1. Gordon, R. L., "A Random Number Generator for Use in
   Fortran V Programs", USL Tech. Memo. No. 2242-320-68,
   6 Sept 1968.

2. Martin, F. F., Computer Modeling and Simulation,
   J. Wiley & Sons, Inc., New York 1968.

3. Dertouzoa, M. L., Kaliski, N. E., and Polzen, K. P.,
   "On-Line Simulation of Block-Diagram Systems", IEEE
   Transactions on Computers, Vol. C-18, No. 4, April 1969,
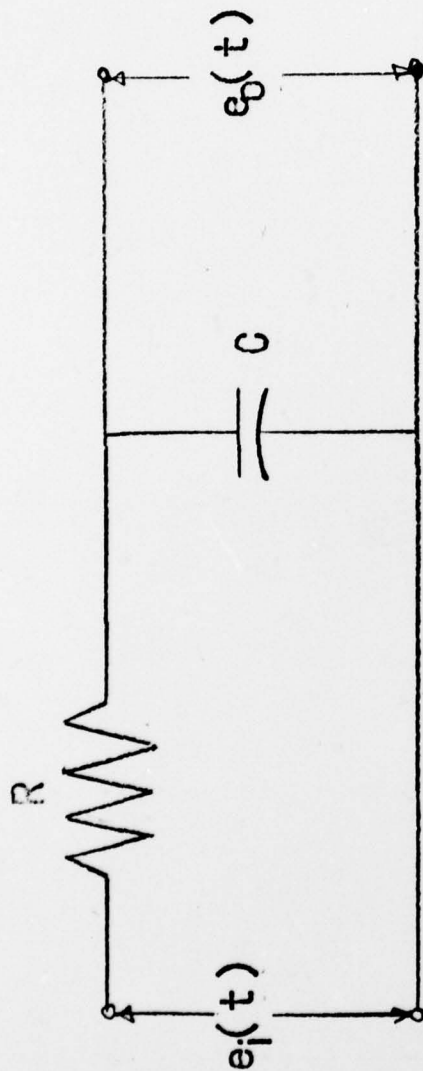   pp 333-342.

PHYSICAL MODELS

Scale Ship Studies

1108 CPU Section

3 - Bit

Replica Corr.
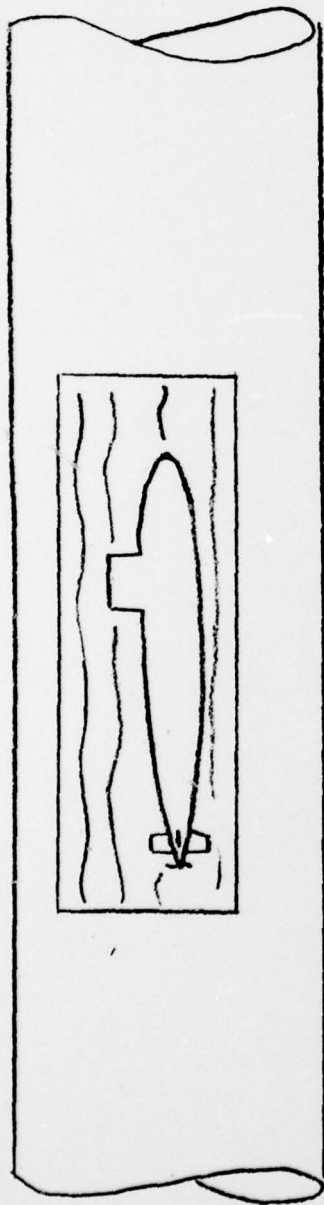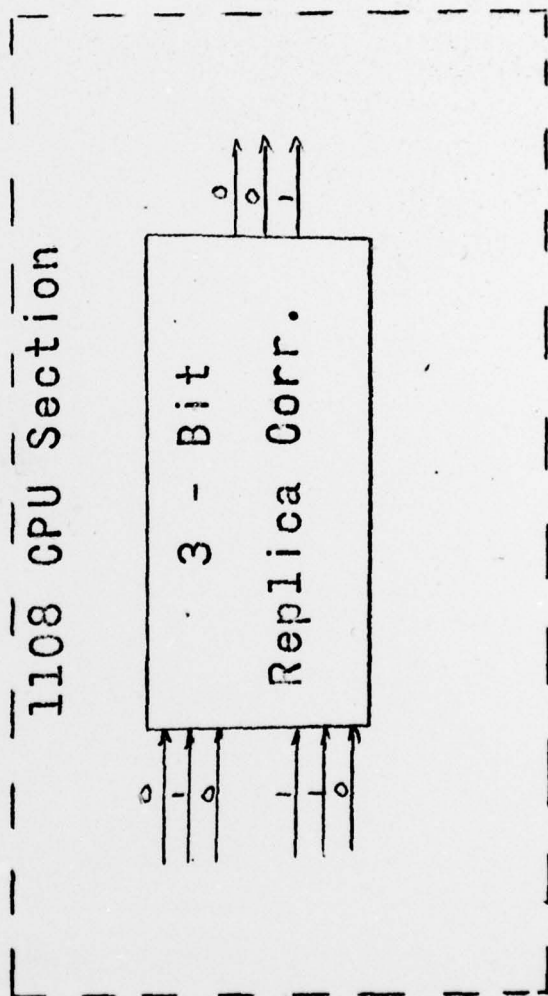
Scaled Digital Hardware Studies

FIGURE 1.

DETERMINISTIC MATHEMATICAL MODELS

$$T \frac{de_0}{dt} + e_0 = e_i \qquad T = RC$$

FIGURE 2.

STOCHASTIC INTEGRATION MODEL

FIGURE 3.

$f(x) = x$

No

(0.3, 0.7)

Yes

$$\frac{Yes}{Yes+No} \approx \int_0^1 x \, dx$$

x

1.0   0.5   1.0

1.0

0.5

0.0
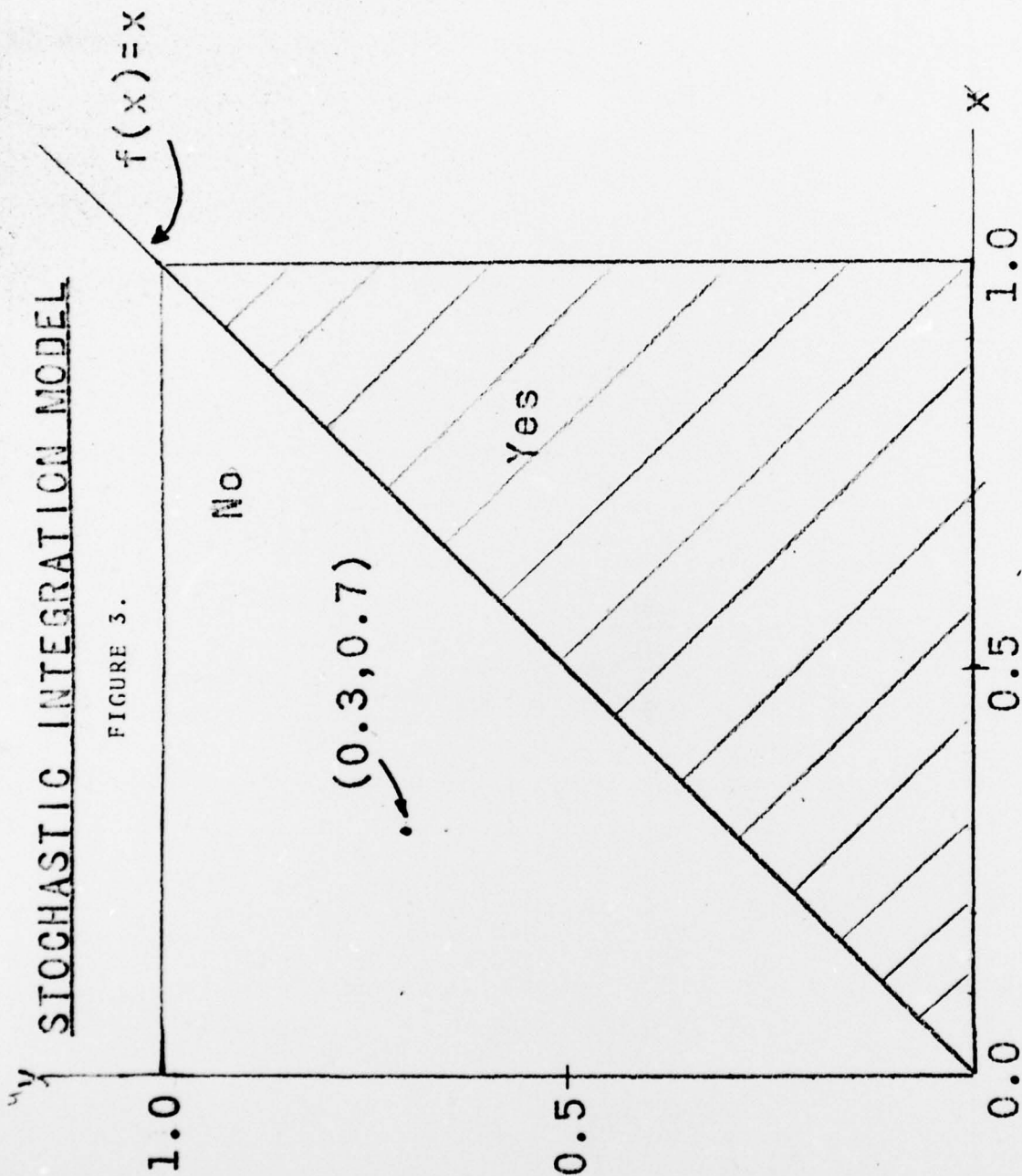
STOCHASTIC EVENT MODEL
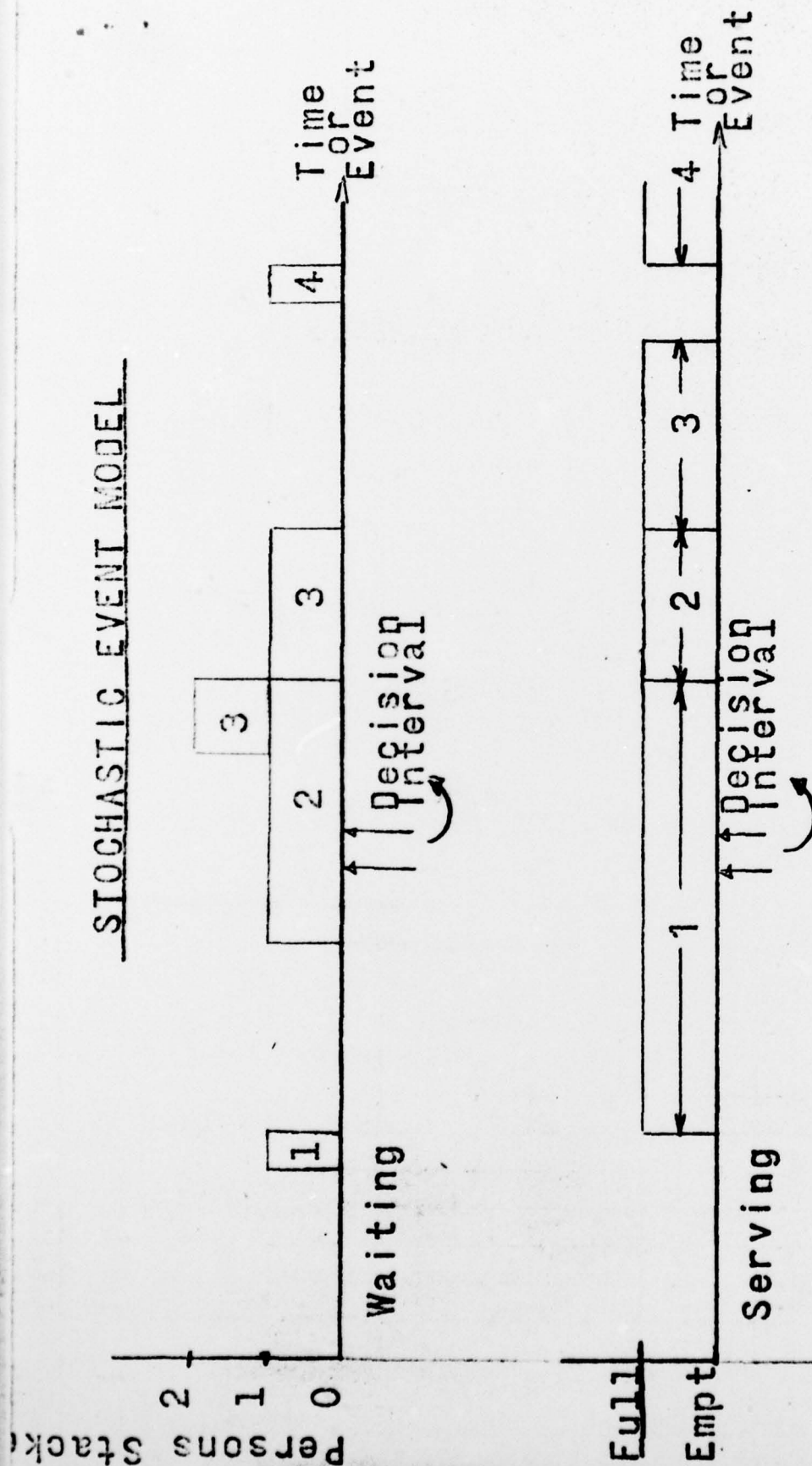
Average Service Time?
Average Number Waiting?

FIGURE 4.